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FEASIBILITY STUDY OF ROBOTIC NEURAL CONTROLLERS

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ABSTRACT

This work is the result of a feasibility study performed to establish if an artificial neural controller could be used to achieve joint space trajectory tracking of a two-link robot manipulator. This study is based on the results obtained by Hecht-Nielsen [4], who claims that a functional map can be implemented to a desired degree of accuracy with a three-layer feedforward artificial neural network. Central to this study is the assumption that the robot model as well as its parameters values are known.

INTRODUCTION

The recent explosion of artificial neural networks applications in virtually every science and engineering discipline has motivated control engineers to look into the possibility of using these types of networks to solve problems whose solutions are very hard to find [1], e.g., a robust controller for a nonlinear system.

Researchers [2,3] have already shown that multilayer feedforward artificial neural networks can be used to solve pattern recognition (mapping) problems. Furthermore, Hecht-Nielsen [4] has "shown" mathematically that an L_2 function (mapping) from $[0,1]^n$ to \mathbb{R}^m can be implemented to any desired degree of accuracy with a three-layer feedforward artificial neural network.

Let us now consider the dynamic model of an n-degree of freedom robot manipulator with revolute joints given by

$$\tau = M(\theta)\ddot{\theta} + V(\theta, \dot{\theta}) + F(\dot{\theta}) + G(\theta) , \quad (1)$$

where τ Δ nx1 vector of joint torques.
 $\theta, \dot{\theta}$ and $\ddot{\theta}$ Δ nx1 vectors representing the angular positions, velocities and accelerations, respectively, of the links.
 $M(\theta)$ Δ nxn inertia matrix.
 $V(\theta, \dot{\theta})$ Δ nx1 vector of torques arising from centripetal and coriolis forces.
 $F(\dot{\theta})$ Δ nx1 friction torque vector.
 $G(\theta)$ Δ nx1 vector of torques due to gravity.

Let

$$f(\theta, \dot{\theta}, \ddot{\theta}) \Delta M(\theta)\ddot{\theta} + V(\theta, \dot{\theta}) + F(\dot{\theta}) + G(\theta) ,$$

then

$$\tau = f(\theta, \dot{\theta}, \ddot{\theta}) . \quad (2)$$

If f is a continuously differentiable function, i.e., every term on the right-hand side of (1) is continuously differentiable (this is a somewhat restrictive requirement for a practical manipulator), then in the light of the result obtained by Hecht-Nielsen [4] the function f that represents the robot dynamics can be implemented (identified) with a three-layer feedforward artificial neural network.

Let $N_f[\theta, \dot{\theta}, \ddot{\theta}; w]$ denote the feedforward artificial neural network that identifies $f(\theta, \dot{\theta}, \ddot{\theta})$, where w represents the weights or input strengths to the artificial neurons, then if the number of neurons in the hidden layer increases to infinity, $N_f \rightarrow f$ (see [5]). Furthermore, if

$$\tau = N_f[\theta, \dot{\theta}, \ddot{\theta}; w] + \dot{e} + k_p e , \quad (3)$$

where $e \triangleq \theta_r - \theta$,
 $\theta_r \triangleq nx1$ vector of reference trajectories,
 $k_p \triangleq nxn$ diagonal positive definite matrix,

then upon substitution of (3) into (1) yields $\dot{e} + k_p e = 0$ also, i.e., $e \rightarrow 0$ which implies that $\theta \rightarrow \theta_r$.

The controller (3) is the equivalent of the well-known method of computed torque [6].

IDENTIFICATION OF ROBOT DYNAMICS USING ARTIFICIAL NEURAL NETWORKS

Consider the two-link direct drive robot manipulator shown in Fig. 1.

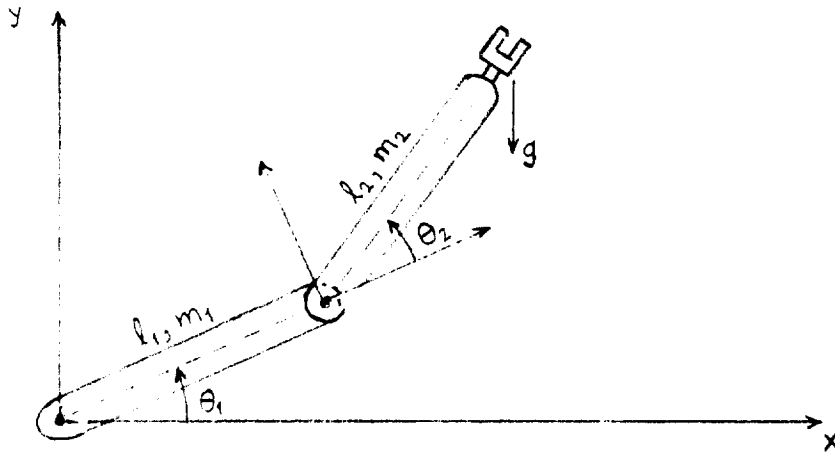


Fig. 1. Two-link robot manipulator.

The dynamic model of this manipulator (excluding friction and external loads) is given by [7]

$$\begin{bmatrix} \tau_1 \\ \tau_2 \end{bmatrix} = \begin{bmatrix} a_1 + a_2 \cos \theta_2 & a_3 + \frac{a_2}{2} \cos \theta_2 \\ a_3 + \frac{a_2}{2} \cos \theta_2 & a_3 \end{bmatrix} \begin{bmatrix} \ddot{\theta}_1 \\ \ddot{\theta}_2 \end{bmatrix} + \begin{bmatrix} -a_2 \left(\dot{\theta}_1 \dot{\theta}_2 + \frac{\dot{\theta}_2^2}{2} \right) \sin \theta_2 \\ \frac{a_2}{2} \dot{\theta}_1^2 \sin \theta_2 \end{bmatrix} + \begin{bmatrix} a_4 \cos \theta_1 + a_5 \cos(\theta_1 + \theta_2) \\ a_5 \cos(\theta_1 + \theta_2) \end{bmatrix} \quad (4)$$

where a_1, \dots, a_5 are constant parameters that depend on the lengths (ℓ_1, ℓ_2) and the masses (m_1, m_2) .

For this particular study, we will use the numerical values of the link parameters that correspond to links 2 and 3 of the Unimation Puma 560 robot manipulator [7], i.e., $\ell_1 = \ell_2 = 0.432$ m; $m_1 = 15.91$ kg and $m_2 = 11.36$ kg. Using these values, we get:

$$\begin{aligned} a_1 &= 3.82 \\ a_2 &= 2.12 \\ a_3 &= 0.71 \\ a_4 &= 81.82 \\ a_5 &= 24.06. \end{aligned}$$

Postulating the problem in the framework of artificial neural networks, we would like to design a network to synthesize the mapping $\tau = f(\theta, \dot{\theta}, \ddot{\theta})$, where

$$f(\theta, \dot{\theta}, \ddot{\theta}) = \begin{bmatrix} (3.82 + 2.12C_2)\ddot{\theta}_1 + (0.71 + 1.06C_2)\ddot{\theta}_2 - 2.12S_2\left(\dot{\theta}_1\dot{\theta}_2 + \frac{1}{2}\dot{\theta}_2^2\right) + 81.82C_1 + 24.06C_{12} \\ (0.71 + 1.06C_2)\ddot{\theta}_1 + 0.71\ddot{\theta}_2 + 1.06S_2(\dot{\theta}_1^2) + 24.06C_{12} \end{bmatrix} \quad (5)$$

where $C_i \triangleq \cos\theta_i$
 $S_i \triangleq \sin\theta_i$
 $C_{ij} \triangleq \cos(\theta_i + \theta_j)$

In our approach we use a so-called connectionist architecture that attempts to identify the complete dynamic equation [8]. This is shown schematically in Fig. 2.

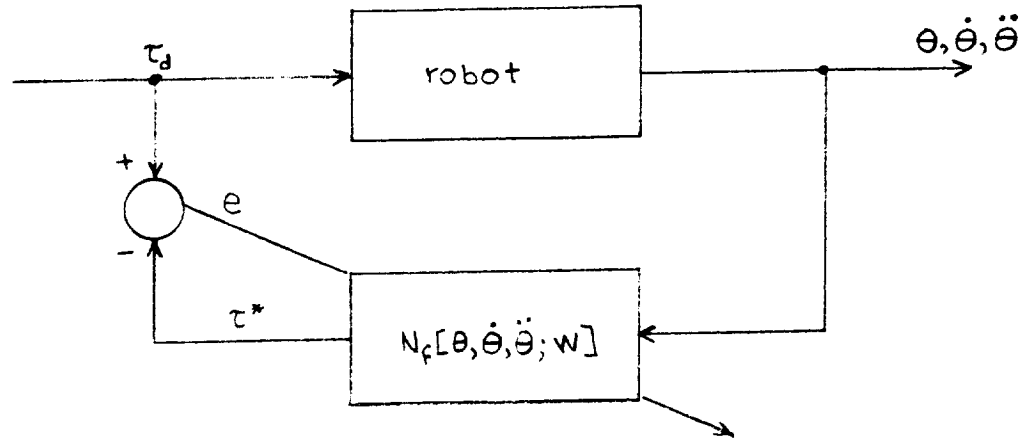


Fig. 2. Learning robot dynamics.

where $\tau_d \triangleq \begin{bmatrix} \tau_{d1} \\ \tau_{d2} \end{bmatrix}$ = desired torques

$\tau^* \triangleq \begin{bmatrix} \tau_1^* \\ \tau_2^* \end{bmatrix}$ = torques generated by the artificial neural network

$e \triangleq \tau_d - \tau^*$

Although the input and output spaces for the two-degree of freedom manipulator is not as large as that of a six-degree of freedom one, it was found experimentally using 4000 8-tuplets (inputs), a four-layer feedforward network with 200, 300, and 400 neurons in each of the two hidden layers and several learning rates (0.7, 0.8, 0.9, 1.0, 1.1), that learning stalled at about 10% of the input-output pairs. In fact, every one of these training runs took several days to execute.

We would also like to point out that three-layer networks with a large number of neurons in the hidden layer were found to perform even worse than the four-layer networks.

It therefore appears that multilayered feedforward artificial neural networks as presently formulated are not of practical use in the identification and control of relatively simple robotic manipulators despite the claims made by many researchers.

CONCLUSIONS

Although Hecht-Nielsen [4] "has proved" that a function (map) can be implemented to a desired degree of accuracy with a three-layer feedforward artificial neural network, a great deal of care must be exercised in interpreting his result, because a very large number of neurons in the hidden layer may be required to learn a functional map, thus rendering these types of networks impractical to implement true neural controllers for robotic manipulators. Therefore, in the opinion of the author, feedforward artificial neural networks as presently conceived, are of no practical use to control robots.

REFERENCES

- [1] P.J. Antsaklis, "Neural Networks in Control Systems," *IEEE Control Systems Magazine*, Vol. 10, No. 3, 1990.
- [2] T.J. Sejnowski and C.R. Rosenberg, "Parallel Networks that Learn to Pronounce English Text," *Complex Syst.*, Vol. 1, pp. 145-168, 1987.
- [3] B. Widrow, R.G. Winter, and R.A. Baxter, "Layered Neural Nets for Pattern Recognition," *IEEE Trans. Assp.*, Vol. 36, No. 7, pp. 1109-1118, July 1988.
- [4] R. Hecht-Nielsen, "Theory of Backpropagation Neural Network," *Proc. IEEE 1989 Intl. Conf. on Neural Networks*, pp. I-593 to I-605.
- [5] M. Arai, "Mapping Abilities of Three-Layer Neural Networks," *Proc. IEEE 1989 Intl. Conf. on Neural Networks*, pp. I-419 to I-423.
- [6] J.J. Craig, *Adaptive Control of Mechanical Manipulators*, Addison-Wesley, 1988.
- [7] H. Seraji, "Decentralized Adaptive Control of Manipulators: Theory, Simulation, and Experimentation," *IEEE Trans. Robotics and Automation*, Vol. 5, No. 2, April 1989.
- [8] D.F. Bassi and G.A. Bekey, "High Precision Position Control by Cartesian Trajectory Feedback and Connectionist Inverse Dynamics Feedforward," *Proc. IEEE 1989 Intl. Conf. on Neural Networks*, pp. II-325 to II-331.